Mitigating Sybils in Federated Learning Poisoning

Clement Fung
University of British Columbia
clement.fung@alumni.ubc.ca

Chris J.M. Yoon
University of British Columbia
yoon@alumni.ubc.ca

Ivan Beschastnikh
University of British Columbia
bestchai@cs.ubc.ca

***Abstract*—Machine learning (ML) over distributed multi-party data is required for a variety of domains. Existing approaches, such as federated learning, collect the outputs computed by a group of devices at a central aggregator and run iterative algorithms to train a globally shared model. Unfortunately, such approaches are susceptible to a variety of attacks, including model poisoning, which is made substantially worse in the presence of sybils.**

In this paper we first evaluate the vulnerability of federated learning to sybil-based poisoning attacks. We then describe *FoolsGold*, a novel defense to this problem that identifies poisoning sybils based on the diversity of client updates in the distributed learning process. Unlike prior work, our system does not bound the expected number of attackers, requires no auxiliary information outside of the learning process, and makes fewer assumptions about clients and their data.

In our evaluation we show that FoolsGold exceeds the capabilities of existing state of the art approaches to countering sybil-based label-flipping and backdoor poisoning attacks. Our results hold for different distributions of client data, varying poisoning targets, and various sybil strategies.

1. Introduction

To train multi-party machine learning (ML) models from user-generated data, users must provide and share their training data, which can be expensive or privacy-violating. Federated learning [26], [27] is a recent solution to both problems: while training across mobile devices, data is kept on the client device and only model parameters are transferred to a central aggregator. This allows clients to compute their model updates locally and independently, while maintaining a basic level of privacy.

However, federated learning introduces a risky design tradeoff: clients, who previously acted only as passive data providers, can now observe intermediate model state and contribute arbitrary updates as part of the decentralized training process. This creates an opportunity for malicious clients to manipulate the training process with little restriction. In particular, adversaries posing as honest clients can send erroneous updates that maliciously influence the properties of the trained model, a process that is known as *model poisoning*.

Poisoning attacks have been well explored in centralized settings and two prevalent examples are *label-flipping attacks* [9], [23] and *backdoor attacks* [4], [14], [20]. In both types of attacks, the larger the proportion of poisoning data, the higher the attack effectiveness. In a federated learning context, where each client maintains data locally, an adversary can naturally increase their attack effectiveness by using *sybils* [17].

TABLE 1. THE ACCURACY AND ATTACK SUCCESS RATES FOR BASELINE (NO ATTACK), AND ATTACKS WITH 1 AND 2 SYBILS IN A FEDERATED LEARNING CONTEXT WITH MNIST DATASET.

	Baseline	Attack 1	Attack 2
# honest clients	10	10	10
# malicious sybils	0	1	2
Accuracy (digits: 0, 2-9)	90.2%	89.4%	88.8%
Accuracy (digit: 1)	96.5%	60.7%	0.0%
Attack success rate	0.0%	35.9%	96.2%

A federated learning poisoning experiment. We illustrate the vulnerability of federated learning to sybil-based poisoning with three experiments based on the setup in Figure 1 and show the results in Table 1. First, we recreate the baseline evaluation in the original federated learning paper [26] and train an MNIST [24] digit classifier across non-IID data sources (Figure 1(a) and Baseline column in Table 1). We train a softmax classifier across ten honest clients, each holding a single digit partition of the original ten-digit MNIST dataset. Each model is trained for 3000 synchronous iterations, in which each client performs a local SGD update using a batch of 50 randomly sampled training examples.

We then re-run the baseline evaluation with a label-flipping 1-7 poisoning attack [7]: each malicious client in the system has a poisoned dataset of 1s labeled as 7s (Figure 1(b)). A successful attack generates a model that is unable to correctly classify 1s and incorrectly predicts them to be 7s. We define the *attack success rate* as the proportion of 1s predicted to be 7s by the final model in the test set. We perform two experiments, in which 1 or 2 malicious sybil clients attack the shared model (Attack 1 and Attack 2 in Table 1).

Table 1 shows that with only 2 sybils, 96.2% of 1s are predicted as 7s in the final shared model. Since one honest client held the data for digit 1, and two malicious sybils held the poisoned 1-7 data, the malicious sybils were twice as influential on the shared model as the honest client. This attack illustrates a problem with federated learning: *all clients have equal influence* on the system[1]. As a result, regardless of the number of honest clients in a federated learning system, with enough sybils an adversary may

1. The only weight in federated learning is the number of examples that each client possesses, but this weight is easy for adversaries to inflate by generating more data or by cloning their dataset.

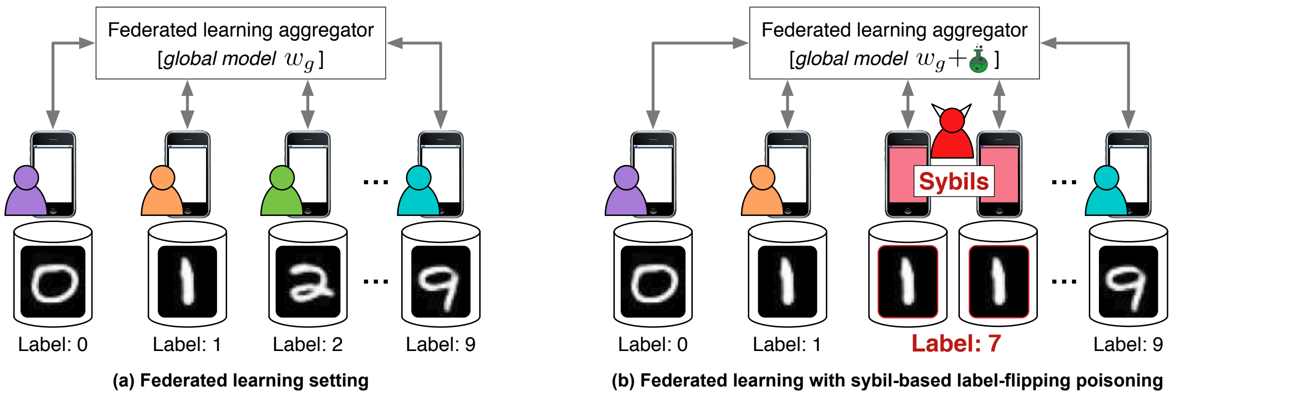

Federated learning aggregator
[global model w_g]
Label: 0
Label: 1
Label: 2
Label: 9
(a) Federated learning setting
Federated learning aggregator
[global model w_g+]
Sybils
Label: 0
Label: 1
Label: 7
Label: 9
(b) Federated learning with sybil-based label-flipping poisoning

Figure 1. Federated learning with and without colluding sybils mounting a sybil-based poisoning attack. In the attack (b) two sybils poison the model by computing over images of 1s with the (incorrect) class label 7.

overpower these honest clients and succeed in poisoning the model.

Known defenses to poisoning attacks in a centralized context, such as robust losses [21] and anomaly detection [35], assume control of the clients or explicit observation of the training data. Neither of these assumptions apply to federated learning in which the server only observes model parameters sent as part of the iterative ML algorithm. Therefore, *these defenses cannot be used in federated learning*.

Poisoning defenses that do apply to federated learning require explicit bounds on the expected number of sybils [10], [36]. To the best of our knowledge, we are the first to mitigate sybil-based poisoning attacks without an explicit parameter for the number of attackers.

Since the federated learning server is unable to view client training data and does not have a validation dataset, the server cannot easily verify which client parameter updates are genuine. Furthermore, these updates are a product of a random stochastic process and will exhibit high variance. We propose **FoolsGold**: a new defense against federated learning sybil attacks that adapts the learning rate of clients based on *contribution similarity*. The insight in this work is that when a shared model is manipulated by a group of sybils, they will, in expectation over the entire training process, contribute updates towards a specific malicious objective, exhibiting behavior that is more similar than expected.

FoolsGold defends federated learning from attacks performed by an arbitrary number of sybils with minimal change to the original federated learning procedure. Moreover, FoolsGold does not assume a specific number of attackers. We evaluate FoolsGold on 4 diverse data sets (MNIST [24], VGGFace2 [13], KDDCup99 [16], Amazon Reviews [16]) and 3 model types (1-layer Softmax, Squeezenet, VGGNet) and find that our approach mitigates label-flipping and backdoor attacks under a variety of conditions, including different distributions of client data, varying poisoning targets, and various sybil strategies.

In summary, we make the following contributions:

- ⋆ We consider sybil attacks on federated learning architectures and show that existing defenses against malicious adversaries in ML (Multi-Krum [10] and RONI [6] (shown in Appendix B)) are inadequate.
- ⋆ We design, implement, and evaluate a novel defense against sybil-based poisoning attacks for the federated learning setting that uses an adaptive learning rate per client based on inter-client contribution similarity.
- ⋆ In this context, we discuss optimal and intelligent attacks that adversaries can perform, while suggesting possible directions for further mitigation.

2. Background

Machine Learning (ML). Many ML problems can be represented as the minimization of a loss function in a large Euclidean space. For an ML binary classification task that predicts a discrete binary output; more prediction errors result in a higher loss. Given a set of training data and a proposed model, ML algorithms *train*, or find an optimal set of parameters, for the given training set.

Stochastic gradient descent (SGD). One approach in ML is to use stochastic gradient descent (SGD) [12], an iterative algorithm that selects a batch of training examples, uses them to compute gradients on the parameters of the current model, and takes gradient steps in the direction that minimizes the loss function. The algorithm then updates the model parameters and another iteration is performed. SGD is a general learning algorithm that can be used to train a variety of models, including deep learning models [12]. We assume SGD as the optimization algorithm in this paper.

In SGD, the model parameters w are updated at each iteration t as follows:

$$w_{t+1} = w_t - \eta_t(\lambda w_t + \frac{1}{b}\sum_{(x_i,y_i)\in B_t} \nabla l(w_t, x_i, y_i)) \qquad (1)$$

where η_t represents a local learning rate, λ is a regularization parameter that prevents over-fitting, B_t represents a gradient batch of training data examples (x_i, y_i) of size b and ∇l represents the gradient of the loss function.

Batch size is what separates SGD from its counterpart, gradient descent (GD). In GD, the entire dataset is used to compute the gradient direction, but in SGD, a subset is used at each iteration. This subset may be selected in a pre-determined order or sampled randomly, but the overall effect of SGD is that the gradient directions seen over time vary (and have higher variance as the batch size b decreases). In practice, SGD is preferred to GD for several reasons: it is less expensive for large datasets and theoretically scales to datasets of infinite size.

A typical heuristic involves running SGD for a fixed number of iterations or halting when the magnitude of the gradient falls below a threshold. When this occurs, model training is completed and the parameters w_t are returned as the optimal model w^*.

Federated learning [26]. In FoolsGold, we assume a standard federated learning context, in which data is distributed across multiple data owners and cannot be shared. The distributed learning process is performed in *synchronous update rounds* over a set of clients, in which a weighted average of the k client updates, based on their proportional training set size n_k out of n total examples, is applied to the model atomically.

$$w_{g,t+1} = w_{g,t} + \sum_k \frac{n_k}{n} \Delta_{k,t}$$

Even if the training data is distributed such that it is not independent and identically distributed (non-IID), federated learning can still attain convergence. For example, federated learning can train an MNIST [24] digit recognition classifier in a setting where each client only held data for 1 of the digit classes (0-9), as in Figure 1(a).

Federated learning comes in two forms: FEDSGD, in which each client sends every SGD update to the server, and FEDAVG, in which clients locally batch multiple iterations of SGD before sending updates to the server, which is more communication efficient. We show that FoolsGold can be applied successfully on both algorithms.

Federated learning also enables model training across a set of clients with highly private data. For example, differentially private [18] and securely aggregated [11] additions have been released, yet the use of federated learning in multi-party settings still presents new privacy and security vulnerabilities [4], [22], [32]. In this paper we design FoolsGold to address sybil-based poisoning attacks.

Targeted poisoning attacks on ML. In a targeted poisoning attack [7], [28], an adversary meticulously creates poisoned training examples and inserts them into the training data set of an attacked model. This is done to increase/decrease the probability of the trained model predicting a targeted example as a targeted class [23] (see Figure 1(b)). For example, such an attack could be mounted to avoid fraud detection or to evade email spam filtering [30].

In FoolsGold, we consider targeted attacks of two types. In *label-flipping attacks* [9], the labels of honest training examples of one class are flipped to another class while the features of the data are kept unchanged. In *backdoor attacks* [4], [20], single features or small regions of the original training data are augmented with a secret pattern and relabeled. The pattern acts as a trigger for the target class, which is exploited by an attacker. Generally, it is important for a poisoning attack to not significantly change the prediction outcomes of other classes. Otherwise, the attack will be detected by users of the shared model.

In federated learning, the aggregator does not see any training data, and we therefore view poisoning attacks from the perspective of model updates: a subset of updates sent to the model at any given iteration are poisoned [10]. This is functionally identical to a centralized poisoning attack in which a subset of the total training data is poisoned. Figure 2 illustrates a targeted poisoning attack in a federated learning context.

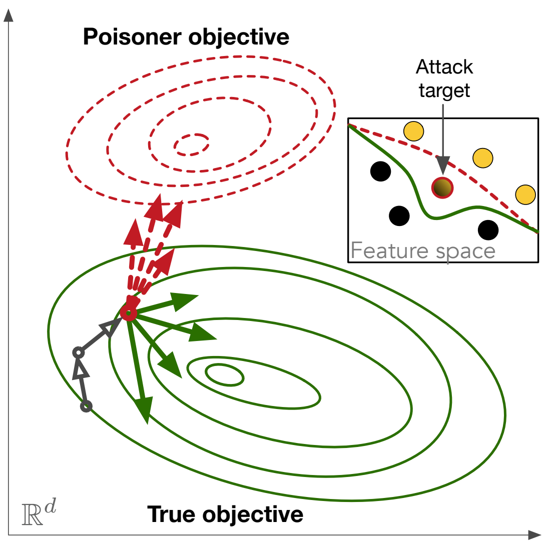


Figure 2. Targeted poisoning attack in SGD. The dotted red vectors are sybil contributions that drive the model towards a poisoner objective. The solid green vectors are contributed by honest clients that drive towards the true objective.

Sybil attacks. A system that allows clients to join and leave is susceptible to sybil attacks [17], in which an adversary gains influence by joining a system under multiple colluding aliases. In FoolsGold, we assume that adversaries leverage sybils to mount more powerful poisoning attacks on federated learning.

3. Assumptions and threat model

Setting assumptions. We are focused on federated learning and therefore assume that data is distributed and hidden across clients. The adversary can only access and influence ML training state through the federated learning API, and adversaries cannot observe the training data of other honest clients.

This means that by observing the total change in model state, adversaries can observe the total averaged gradient across all clients, but they cannot view the gradient of any individual honest client.

On the server side of the algorithm, we assume that the aggregator is uncompromised and is not malicious. Similarly, we assume that some number of honest clients, who possess training data which opposes the attacker's poisoning goal, participate in the system. More precisely, our solution requires that every class defined by the model is represented in the data of at least one honest client. Without these honest clients, no contribution-based defense is possible since the model would be unable to learn anything about these classes in the first place.

Secure-aggregation for federated learning provides better privacy by obfuscating individual client updates [11]. We assume that these types of obfuscations are not used, and that the central server is able to observe any individual client's model update at each iteration.

Poisoning attacks. In our setting, targeted poisoning attacks are performed by adversaries against the globally trained model. An adversary has a defined poisoning goal: increase the probability of one class being classified as a different, incorrect class without influencing the output probabilities of any other class. To minimize the possibility of the poisoning attack being detected, the prediction outcomes of classes auxiliary to the attack should be minimally changed.

We assume that poisoning attacks are performed using either the label-flipping strategy [9], in which the labels of honest training examples are flipped to a target class, or the backdoor strategy [4], [20], in which unused features are augmented with secret patterns and exploited.

Since the range of possible SGD updates from an adversary is unbounded, another possible attack involves scaling malicious updates to overpower honest clients. However, state of the art magnitude-based detection methods exist [10] to prevent these attacks, and therefore we do not consider these attacks.

Sybils perform poisoning attacks on federated learning by providing updates that direct the shared model towards a common poisoned objective, as shown in Figure 2. We do not constrain how a sybil selects these poisoned updates: they can be sourced from poisoned data [7] or computed through other methods.

Attacker capability. For a poisoning attack to succeed in a deployment with many honest clients, an attacker must exert more influence on their target class than the total honest influence on this class. This is already a problem for classes that are not well represented in the training data, but in federated learning, where each client is given an equal share of the aggregated gradient, attackers can attack any class with enough influence by generating additional sybils.

If a third party account verification process exists in the system, we assume that the adversary has the means to bypass it, either by creating malicious accounts or by compromising honest clients/accounts.

Sybils observe global model state and send any arbitrary gradient contribution to aggregator at any iteration. Sybils can collude by sharing state among themselves and by sending updates in an intelligent, coordinated fashion. Sybils controlled by multiple sets of non-colluding adversaries may perform poisoning attacks concurrently.

4. SGD Challenges and defenses

In the traditional federated learning setting, the federated learning service only has access to the outputs of local SGD computations. From the aggregator's perspective, detecting sybils from a stream of SGD iterations is difficult. If GD, and not SGD, is used as the optimization algorithm, then detection becomes easier: in this setting, updates are deterministic functions of data and duplicate updates are easy to detect. The challenge with SGD is three-fold:

Challenge 1. Each client houses a local, unseen partition of the data that independently may not satisfy the global learning objective. When receiving a gradient from a client, it is difficult for the aggregator to tell whether the gradient points towards a malicious objective or not. We assume that FoolsGold, the system we design, does not possess a validation dataset.

Challenge 2. Since only a small subset of the original dataset is used in each iteration, the stochastic objective changes with each iteration. The aggregator cannot assume that updates pointing in sporadic directions are malicious. As well, the aggregator cannot assume that updates that are similar came from similar underlying datasets.

Challenge 3. As the batch size b of updates decreases, the variance of updates contributed by clients increases. At any given iteration, sampling a smaller portion of the dataset results in a higher variance of gradient values, producing the sporadic behavior described above. Since adversaries can send arbitrary updates to the model, we cannot trust that they will conform to a specified batch size configuration.

The challenges above make existing poisoning defenses ineffective against sybil-based attacks on federated learning, particularly in non-IID settings.

Multi-Krum [10] was specifically designed to counter adversaries in federated learning. In Multi-Krum, the top f contributions to the model that are furthest from the mean client contribution are removed from the aggregated gradient. Multi-Krum uses the Euclidean distance to determine which gradient contributions are removed, requires parameterization of the number of expected adversaries, and can theoretically only withstand sybil-based poisoning attacks of up to 33% adversaries in the client pool.

We assume that attackers can spawn a large number of sybils, rendering assumptions about proportions of honest clients unrealistic. As well, the mean in the Multi-Krum process can be arbitrarily influenced by sybil contributions. We compare FoolsGold against Multi-Krum in Section 6.2.

5. FoolsGold design

Our solution is intended for a federated learning setting where the service only has access to the outputs of client SGD computations. We design a learning method that does not make assumptions about the proportion of honest clients in the system. Our learning method only uses state from the learning process itself to adapt the learning rates of clients.

Our key insight is that *honest clients can be separated from sybils by the diversity of their gradient updates*. In federated learning, since each client's training data has a unique distribution and is not shared, sybils share a common objective and will contribute updates that appear more similar to each other than honest clients. This property of federated learning is shown in Figure 6 and explored in Section 6.3.

FoolsGold uses this assumption to modify the learning rates of each client in each iteration. Our approach aims to maintain the learning rate of clients that provide unique gradient updates, while reducing the learning rate of clients that repeatedly contribute similar-looking gradient updates.

With this in mind, FoolsGold has five design goals:

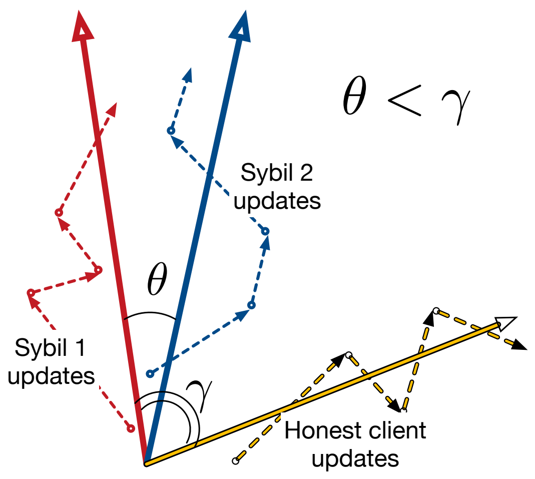


Figure 3. Dashed lines are gradient updates from three clients (2 sybils, 1 honest). Solid lines are aggregated update vectors. The angle between the aggregated update vectors of sybil clients (θ) is smaller than between those of the honest client and a sybil (γ). Cosine similarity would reflect this similarity.

Goal 1. When the system is not attacked, FoolsGold should preserve the performance of federated learning.

Goal 2. FoolsGold should devalue contributions from clients that point in similar directions.

Goal 3. FoolsGold should be robust to an increasing number of sybils in a poisoning attack.

Goal 4. FoolsGold should distinguish between honest updates that mistakenly appear malicious due to the variance of SGD and sybil updates that operate on a common malicious objective.

Goal 5. FoolsGold should not rely on external assumptions about the clients or require parameterization about the number of attackers.

We now explain the FoolsGold approach (Algorithm 1). In the federated learning protocol, gradient updates are collected and aggregated in synchronous update rounds. FoolsGold adapts the learning rate α_i per client[2] based on (1) the update similarity among indicative features in any given iteration, and (2) historical information from past iterations.

Cosine similarity. We use cosine similarity to measure the angular distance between updates. This is preferred to Euclidean distance since sybils can manipulate the magnitude of a gradient to achieve dissimilarity, but the direction of a gradient cannot be manipulated without reducing attack effectiveness. The magnitude of honest updates is also affected by client-side hyper-parameters, such as the local learning rate, which we do not control.

Feature importance. From the perspective of a potential poisoning attack, there are three types of features in the model: (1) features that are relevant to the correctness of the model, but must be modified for a successful attack, (2) features that are relevant to the correctness of the model, but irrelevant for the attack, and (3) features that are irrelevant to both the attack and the model.

```
Data: Global Model $w^t$ and SGD update $\Delta_{i,t}$
      from each client $i$ at iteration $t$. Confidence
      parameter $\kappa$
1  for Iteration $t$ do
2      for All clients $i$ do
           // Updates history
3          Let $H_i$ be the aggregate historical vector
             $\sum_{t=1}^{T} \Delta_{i,t}$
           // Feature importance
4          Let $S_t$ be the weight of indicative features
             at iteration $t$
5          for All other clients $j$ do
6              Let $cs_{ij}$ be the $S_t$-weighted cosine
                 similarity between $H_i$ and $H_j$
7          end
8          Let $v_i = \max_j(cs_i)$
9      end
10     for All clients $i$ do
11         for All clients $j$ do
               // Pardoning
12             if $v_j > v_i$ then
13                 $cs_{ij} *= v_i / v_j$
14             end
15         end
           // Row-size maximums
16         Let $\alpha_i = 1 - \max_j(cs_i)$
17     end
       // Logit function
18     $\alpha_i = \alpha_i / \max_i(\alpha)$
19     $\alpha_i = \kappa(\ln[(\alpha_i)/(1 - \alpha_i)] + 0.5)$
       // Federated SGD iteration
20     $w_{t+1} = w_t + \sum_i \alpha_i \Delta_{i,t}$
21 end
```

Algorithm 1: FoolsGold algorithm.

Similar to other decentralized poisoning defenses [36], we look for similarity only in the indicative features (type 1 and 2) in the model. This prevents adversaries from manipulating irrelevant features while performing an attack, which is evaluated in Section 6.4.

The indicative features are found by measuring the magnitude of model parameters in the output layer of the global model. Since training data features and gradient updates are normalized while performing SGD, the magnitude of an output layer parameter maps directly to its influence on the prediction probability [37]. These features can be filtered (hard) or re-weighed (soft) based on their influence on the model, and are normalized across all classes to avoid biasing one class over another.

For deep neural networks, we do not consider the magnitude of values in the non-output layers of the model, which do not map directly to output probabilities and are more difficult to reason about. Recent work on feature influence in deep neural networks [1], [15] may better capture the intent of sybil-based poisoning attacks in deep learning and we leave this analysis as future work.

Updates history. FoolsGold maintains a history of updates from each client. It does this by aggregating the updates at each iteration from a single client into a single aggregated client gradient (line 3). To better estimate

2. Note that we use α for the FoolsGold assigned learning rate, and η for the traditional, local learning rate. These are independent of each other.

similarity of the overall contributions made by clients, FoolsGold computes the similarity between pairwise aggregated historical updates instead of just the updates from the current iteration.

Figure 3 shows that even for two sybils with a common target objective, updates at a given iteration may diverge due to the problems mentioned in Challenge 2. However, the cosine similarity between the sybils' aggregated historical updates is high, satisfying Goal 2.

We interpret the cosine similarity on the indicative features, a value between -1 and 1, as a representation of how strongly two clients are acting as sybils. We define v_i as the maximum pairwise similarity for a client i, ensuring that as long as one such interaction exists, we can devalue the contribution while staying robust to an increasing number of sybils, as prescribed by Goal 3.

$$cs_{ij} = cosine\_similarity(\sum_{t=1}^{T} \Delta_{i,t}, \sum_{t=1}^{T} \Delta_{j,t})$$

Pardoning. Since we have weak guarantees on the cosine similarities between an honest client and sybils, honest clients may be incorrectly penalized under this scheme. We introduce a pardoning mechanism that avoids penalizing such honest clients by re-weighing the cosine similarity by the ratio of v_i and v_j (line 13), satisfying Goal 4. The new client learning rate α_i is then found by inverting the maximum similarity scores along the 0-1 domain. Since we assume at least one client in the system is honest, we rescale the vector such that the maximum adaption of the learning rate is 1 (line 18). This ensures that at least one client will have an unmodified update and encourages the system towards Goal 1: a system containing only honest nodes will not penalize their contributions.

$$\alpha_i = 1 - \max_j(cs_i)$$
$$\alpha_i = \frac{\alpha_i}{\max_i(\alpha)}$$

Logit. However, even for very similar updates, the cosine similarity may be less than one. An attacker may exploit this by increasing the number of sybils to remain influential. We therefore want to encourage a higher divergence for values that are near the two tails of this function, and avoid penalizing honest clients with a low, non-zero similarity value. Thus, we use the logit function (the inverse sigmoid function) centered at 0.5 (line 19), for these properties. We also expose a confidence parameter κ that scales the logit function and show in 9 that κ can be set as a function of the data distribution among clients to guarantee convergence.

$$\alpha_i = \kappa(\ln[\frac{\alpha_i}{1-\alpha_i}] + 0.5)$$

When taking the result of the logit function, any value exceeding the 0-1 range is clipped and rounded to its respective boundary value. Finally, the overall gradient update is calculated by applying the final re-scaled learning rate:

$$w_{t+1} = w_t + \sum_i \alpha_i \Delta_{i,t}$$

TABLE 2. DATASETS USED IN THIS EVALUATION.

Dataset	Train Set Size	Classes	Features	Model Used
MNIST	60,000	10	784	1-layer softmax
VGGFace2	7,380	10	150,528	SqueezeNet, VGGNet11
KDDCup	494,020	23	41	1-layer softmax
Amazon	1,500	50	10,000	1-layer softmax

Note that this design does not require parameterization of the expected number of sybils or their properties (Goal 5), is independent of the underlying model, and is also independent of SGD details such as the local client's learning rate or batch size.

Augmenting FoolsGold with other methods. Simply modifying the learning rates of clients based on their aggregate gradient similarity will not handle all poisoning attacks. Clearly, an attack from a single adversary will not exhibit such similarity. FoolsGold is best used when augmented with existing solutions that detect poisoning attacks from a bounded number of attackers. We evaluate FoolsGold with Multi-Krum in Section 7.

Convergence properties. FoolsGold is analagous to importance sampling [29] and adaptive learning rate methods [42], which have both been applied to SGD algorithms and have convergence guarantees. We analyze FoolsGold's convergence guarantees in 9. Our experimental results further support that FoolsGold converges under a variety of conditions.

FoolsGold security guarantees. We claim that our design mitigates an adversary performing a targeted poisoning attack by limiting the influence they gain through sybils. We also claim that FoolsGold satisfies the specified design goals: it preserves the updates of honest nodes while penalizing the contributions of sybils. In the next section we empirically validate these claims across several different dimensions using a prototype of FoolsGold.

6. Evaluation

We evaluate FoolsGold by implementing a federated learning prototype in 600 lines of Python. The prototype includes 150 lines for FoolsGold, implementing Algorithm 1. We use scikit-learn [34] to compute cosine similarity of vectors. For each experiment below, we partition the original training data into disjoint non-IID training sets, locally compute SGD updates on each dataset, and aggregate the updates using the described FoolsGold method to train a globally shared classifier.

We evaluate our prototype on four well-known classification datasets: MNIST [24], a digit classification problem, VGGFace2 [13], a facial recognition problem, KDDCup [16], which contains classified network intrusion patterns, and Amazon [16], which contains a corpus of text from product reviews. Table 2 describes each dataset.

Each dataset was selected for one of its particularities. MNIST was chosen as the baseline dataset for evaluation since it was used extensively in the original federated learning evaluation [26]. The VGGFace2 dataset was chosen as a more complex learning task that required deep neural networks to solve. For simplicity in evaluating poisoning attacks, we limit this dataset to the top 10 most frequent classes only. The KDDCup dataset has a relatively low number of features, and contains a massive class imbalance: some classes have as few as 5 examples, while some have over 280,000. Lastly, the Amazon dataset is unique in that it has few examples and contains text data: each review is converted into its one hot encoding, resulting in a large feature vector of size 10,000.

For all the experiments in this section, targeted poisoning attacks are performed that attempt to encourage a *source label* to be classified as a *target label* while training on a federated learning prototype. When dividing the data, each class is always completely represented by a single client, which is consistent with the federated learning baseline. In all experiments the number of honest clients in the system varies by dataset: 10 for MNIST and VGGFace2, 23 for KDDCup, and 50 for Amazon. We consider more IID settings in Section 6.3.

For MNIST, KDDCup, and Amazon, we train a single layer fully-connected softmax for classification. The size of the trained model in each case is the product of the number of classes and number of features. For VGGFace2, we use two popular architectures pre-trained on Imagenet from the torchvision package [25]: SqueezeNet1.1, a smaller model designed for edge devices with 727,000 parameters; and VGGNet11, a larger model with 128 million parameters. When using FoolsGold to compare client similarity, we only use the features in the final output layer's gradients (fully connected layer in VGGNet and 10 1x1 convolutional kernels in SqueezeNet).

In MNIST, the data is already divided into 60,000 training examples and 10,000 test examples [24]. For VGGFace2, KDDCup and Amazon, we randomly partition 30% of the total data to be test data. The test data is used to evaluate two metrics that represent the performance of our algorithm: the *attack rate*, which is the proportion of attack targets (source labels for label flipping attacks or embedded images for backdoor attacks) that are incorrectly classified as the target label, and the *accuracy*, which is the proportion of examples in the test set that are correctly classified.

The MNIST and KDDCup datasets were executed with 3,000 iterations and a batch size of 50 unless otherwise stated. For Amazon, due to the high number of features and low number of samples per class, we train for 100 iterations and a batch size of 10. For VGGFace2, we train for 500 iterations, using SGD with batch size of 8, momentum 0.9, weight decay 0.0001, and learning rate 0.001. These values were found using cross validation in the training set. During training, images were resized to 256x256 and randomly cropped and flipped to 224x224. During testing, images were resized to 256x256 and a 224x224 center was cropped.

In each of the non-attack scenarios, we ran each experiment to convergence. In all attack scenarios, we found that our selected number of iterations was sufficiently high such that the performance of the attack changed minimally with each iteration, indicating the result of the attack to be consistent. For each experiment, FoolsGold is parameterized with a confidence parameter $\kappa = 1$, and does not use the historical gradient or the significant features filter (we evaluate these design elements independently in Section 6.5 and 6.4, respectively). Each reported data point is the average of 5 experiments.

TABLE 3. CANONICAL ATTACKS USED IN OUR EVALUATION.

Attack	Description	Dataset
A-1	Single client attack.	All
A-5	5 clients attack.	All
A-5x5	5 sets of 5 clients, concurrent attacks.	MNIST, Amazon, VGGFaces2
A-OnOne	5 clients executing 5 attacks on the same target class.	KDDCup99
A-99	99% sybils, performing the same attack.	MNIST

6.1. Canonical attack scenarios

Our evaluation uses a set of 5 attack scenarios (that we term canonical for this evaluation) across the three datasets (Table 3). Attack **A-1** is a traditional poisoning attack: a single client joins the federated learning system with poisoned data. Attack **A-5** is the same attack performed with 5 sybil clients joining the system. Each client sends updates for a subset of its data through SGD, meaning that their updates are not identical. Attack **A-2x5** evaluates FoolsGold's ability to thwart multiple attacks at once: 2 sets of client sybils attack the system concurrently, and for attack evaluation purposes we assume that the classes in these attacks do not overlap[3].

Since KDDCup99 is a unique dataset with severe class imbalance, instead of using an A-2x5 attack we choose to perform a different attack, **A-OnOne**, on this dataset. In KDDCup99, data from various network traffic patterns are provided. Class "Normal" identifies patterns without any network attack, and is proportionally large (approximately 20% of the data) in the overall dataset. Therefore, when attacking KDDCup99, we assume that adversaries mis-label malicious attack patterns, which are proportionally small, (approximately 2% of the data) and poison the malicious class towards the "Normal" class. A-AllOnOne is a unique attack for KDDCup in which 5 different malicious patterns are each labeled as "Normal", and each attack is performed concurrently.

Finally, we use **A-99** to illustrate the robustness of FoolsGold to massive attack scenarios. In this attack, an adversary generates 990 sybils to overpower a network of 10 honest clients and all of them attempt a single 1-7 attack against MNIST.

Since we use these canonical attacks throughout this work, we first evaluate each attack on the respective dataset (Table 3) with FoolsGold enabled. Figure 4 plots the attack rate and test accuracy for each attack in Table 3. The Figure also shows results for the system without attacks: the original federated learning algorithm (FL-NA) and the system with the FoolsGold algorithm (FG-NA).

Figure 4 shows that for most attacks, including the A-OnOne attack and the A-99 attack, FoolsGold effectively prevents the attack while maintaining high training accuracy. As FoolsGold faces larger groups of sybils, it has more information to more reliably detect similarity between sybils. FoolsGold performs worst on the A-1 attacks in which only one malicious client attacked the system. The reason is simple: without multiple colluding

3. We do not perform a 1-2 attack in parallel with a 2-3 attack, since evaluating the 1-2 attack would be biased by the performance of the 2-3 attack.

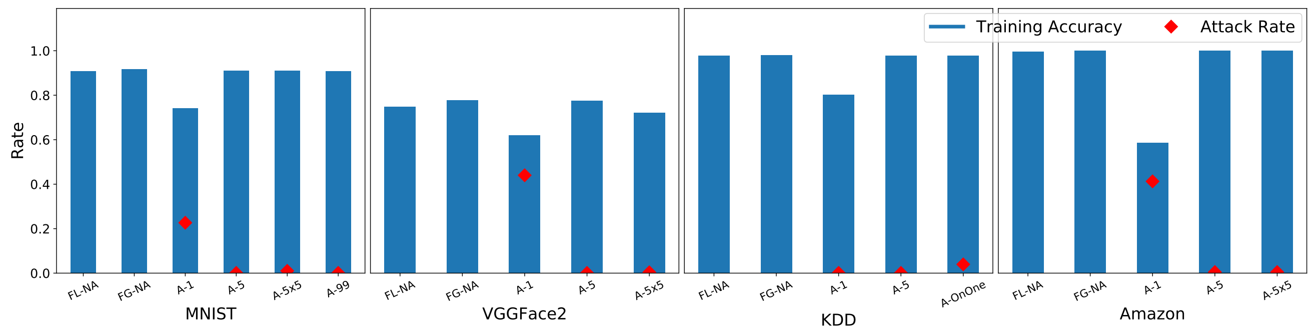


Figure 4. Training accuracy (blue bars) and attack rate (red ticks) for canonical attacks against the relevant canonical datasets.

sybils, malicious and honest clients are indistinguishable to the FoolsGold aggregator.

Another point of interest is the prevalence of false positives. In A-1 KDDCup, our system incorrectly penalized an honest client for colluding with the attacker, lowering the prediction rate of the honest client as the defense was applied. We observe that the two primary reasons for low training error are either a high attack rate (false negatives) or a high target class error rate (false positives). We also discuss false positives from data similarity in Section 6.3.

6.2. Comparison to prior work

We compare FoolsGold to Multi-Krum aggregation [10], the known state of the art in defending against Byzantine clients in distributed SGD (see Section 2).

Comparison to Multi-Krum. In this experiment we compare FoolsGold to Multi-Krum and an unmodified federated learning baseline as we vary the number of sybils.

We implemented Multi-Krum as specified in the original paper [10]: at each iteration, the total Euclidean distance from the $n-f-2$ nearest neighbors is calculated for each update. The f updates with the highest distances are removed and the average of the remaining updates is calculated. Multi-Krum relies on the f parameter: the maximum number of Byzantine clients tolerated by the system. To defend against sybil attacks in this setting, we set f to be the number of sybils executing a poisoning attack. Although this is the best case for Multi-Krum, we note that prior knowledge of f is an unrealistic assumption when defending against sybils.

While running Multi-Krum, we found that the performance was especially poor in the non-IID setting. When the variance of updates among honest clients is high, and the variance of updates among sybils is lower, Multi-Krum removes honest clients from the system. This makes Multi-Krum unsuitable for defending against sybils in federated learning, which is intended for non-IID settings [26].

Figure 5 shows the performance of the three approaches against an increasing number of poisoners: a 1-7 attack is performed on an unmodified non-IID federated learning system (Baseline), a federated learning system with Multi-Krum aggregation, and our proposed solution. We show FoolsGold's effectiveness against both FEDSGD and FEDAVG [26], in which clients perform multiple local iterations before sharing updates with the aggregator.

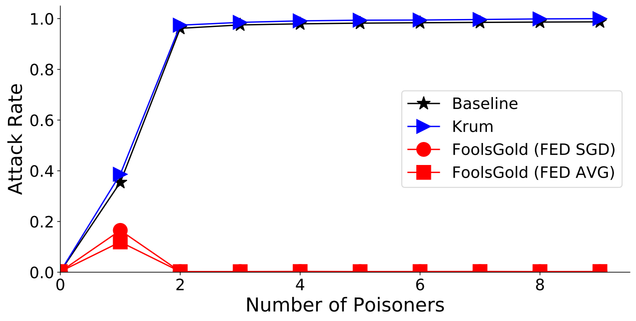


Figure 5. Attack rate for varying number of sybils, for federated learning (Baseline), Multi-Krum, and FoolsGold.

We see that as soon as the proportion of poisoners for a single class increases beyond the corresponding number of honest clients that hold that class (which is 1), the attack rate increases significantly for naive averaging (Baseline).

In addition to exceeding the parameterized number of expected sybils, an adversary can also influence the mean client contribution at any given iteration, and Multi-Krum will fail to distinguish between honest clients and sybils.

Multi-Krum works with up to 33% sybils [10], but fails above this threshold. By contrast, FoolsGold penalizes attackers further as the proportion of sybils increases, and in this scenario FoolsGold remains robust even with 9 attackers.

Consistent with the results in Figure 4, FoolsGold in Figure 5 performs the worst when only one poisoner is present. We also show that FoolsGold similarly outperforms Multi-Krum in defending against backdoor attacks [20] in Appendix B.

6.3. Varying client data distributions

FoolsGold relies on the assumption that training data is sufficiently dissimilar between clients. However, a realistic scenario may involve settings where each client has overlapping data, such as images of the same people.

To test FoolsGold under diverse data distribution assumptions, we conduct an A-5 0-1 attack (with 5 sybils) on MNIST and VGGFace2 with 10 honest clients while varying the proportion of shared data within both the sybils and honest clients. We varied the distribution of sybils and honest clients over a grid $(x_{sybil}, x_{honest} \in \{0, 0.25, 0.5, 0.75, 1\})$, where x refers to the ratio of disjoint data to shared data. Specifically, a proportion of 0% refers to a non-IID setting in which each client's dataset

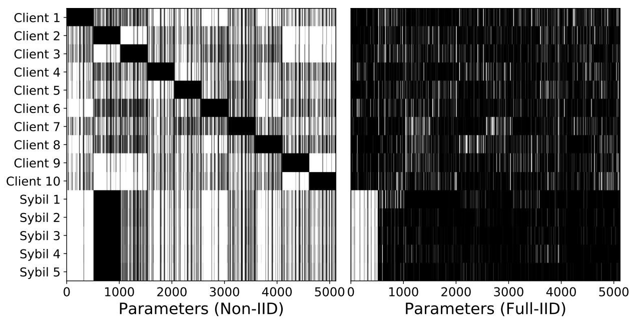
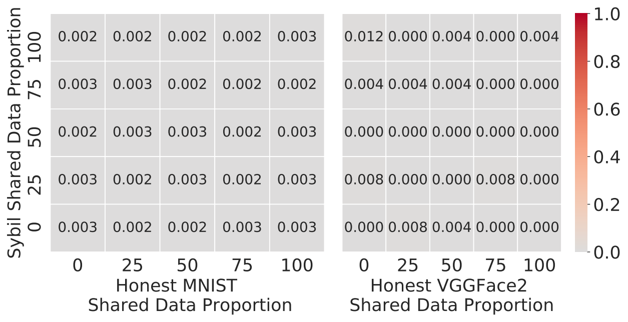


Figure 6. A visualization of the historical gradient of clients in Squeezenet, in the non-IID (left) and IID (right) case. The top 10 rows show the gradient vector of honest clients; the bottom 5 rows for sybils performing a targeted 0-1 attack.



Sybil \ Honest MNIST	0	25	50	75	100
100	0.002	0.002	0.002	0.002	0.003
75	0.003	0.003	0.002	0.002	0.002
50	0.002	0.003	0.003	0.002	0.003
25	0.003	0.002	0.003	0.002	0.003
0	0.003	0.002	0.002	0.003	0.003

Sybil \ Honest VGGFace2	0	25	50	75	100
100	0.012	0.000	0.004	0.000	0.004
75	0.004	0.004	0.004	0.000	0.000
50	0.000	0.000	0.000	0.000	0.000
25	0.008	0.000	0.000	0.008	0.000
0	0.000	0.008	0.004	0.000	0.000

Figure 7. The attack rates on the MNIST and VGGFace2 dataset for varying sybil and honest client data distributions. 0% means that the data is completely disjoint by class; 100% means that the data is uniformly distributed.

is composed of a single class, and 100% refers to a setting where each client's dataset is uniformly sampled from all classes. A proportion of x refers to a setting where clients hold $x\%$ uniform data from all classes and $(1-x)\%$ disjoint data for a specific class. To create a sybil client with $x\%$ shared data, we first create an honest client with $x\%$ shared data and $(1-x)\%$ disjoint data using class 0, and then flip all 0 labels to a 1 to perform a targeted attack.

To understand how FoolsGold handles these situations, we visualize the gradient history of all clients for a VGGFaces2 A-5 experiment in Figure 6. Each row shows the historical gradient of a client in the final classification layer, where the top 10 rows correspond to honest clients and the bottom 5 rows correspond to sybils. The left side of Figure 6 shows the historical gradient in a non-IID setting ($x_{sybil}, x_{honest} = 0$). Since each honest client has data corresponding to a unique class, their gradients are highly dissimilar, and since the sybils have the same poisoning dataset for a 0-1 attack, their gradients are highly similar. Therefore, FoolsGold can easily detect the sybil gradients.

The right side of Figure 6 shows the historical gradient in an IID setting ($x_{sybil}, x_{honest} = 1$). Even when the honest clients all hold uniform samples of the training data, the stochasticity of SGD introduces variance between honest clients, and the sybil gradients are still uniquely distinct as a result of their poisoned data, as seen in the bottom left corners of Figure 6. Sybils that intend to execute a targeted poisoning attack produce fundamentally similar gradient updates, enabling FoolsGold to succeed. We formally define the convergence of FoolsGold by bounds on inter-client update similarity in Appendix A.

FoolsGold is effective at defending against poisoning attacks for all combinations: the maximum attack rate was less than 1% for both the MNIST and VGGFace2 datasets, using both SqueezeNet and VGGNet. We show these results in Figure 7. As the results in this section demonstrate, a malicious actor cannot subvert FoolsGold by manipulating their malicious data distribution. Instead, they must directly manipulate their gradient outputs, which we explore next.

6.4. What if the attacker knows FoolsGold?

If an attacker is aware of the FoolsGold algorithm, they may attempt to send updates in ways that encourage additional dissimilarity. This is an active trade-off: as attacker updates become less similar to each other (lower chance of detection), they become less focused towards the poisoning objective (lower attack utility).

We consider and evaluate four ways in which attackers may attempt to subvert FoolsGold: (1) mixing malicious and correct data, (2) changing sybils' training batch size, (3) perturbing contributed updates with noise, and (4) infrequently and adaptively sending poisoned updates. Due to space constraints, the results of (1) and (2) are listed in Appendix B.

Adding intelligent noise to updates. A set of intelligent sybils could send pairs of updates with carefully perturbed noise that is designed to sum to zero. For example, if an attacker draws a random noise vector ζ, two malicious updates a_1 and a_2 could be contributed as v_1 and v_2, such that: $v_1 = a_1 + \zeta$, and $v_2 = a_2 - \zeta$.

Since the noise vector ζ has nothing to do with the poisoning objective, its inclusion will add dissimilarity to the malicious updates and decrease FoolsGold's effectiveness in detecting them. Also note that the sum of these two updates is still the same: $v_1 + v_2 = a_1 + a_2$. This strategy can also be scaled beyond 2 sybils by taking orthogonal noise vectors and their negation: for any subset of these vectors, the cosine similarity is 0 or -1, while the sum remains 0.

As explained in Section 5, this attack is most effective if ζ is only applied to features of type (3): those which are not important for the model or the attack. This increases sybil dissimilarity and does not adversely impact the attack.

This attack is mitigated by filtering for indicative features in the model. Instead of looking at the cosine similarity between updates across all features in the model, we look at a weighted cosine similarity based on feature importance.

To evaluate the importance of this mechanism to the poisoning attack, we execute the intelligent noise attack described above on MNIST, which contains several irrelevant features (the large black regions) in each example: a pair of sybils send v_1 and v_2 with intelligent noise ζ. We then vary the proportion of model parameters that are defined as indicative from 0.001 (8 features on MNIST) to 1 (all features).

Figure 8 shows the attack rate and the training accuracy for varying proportions of indicative features. We first

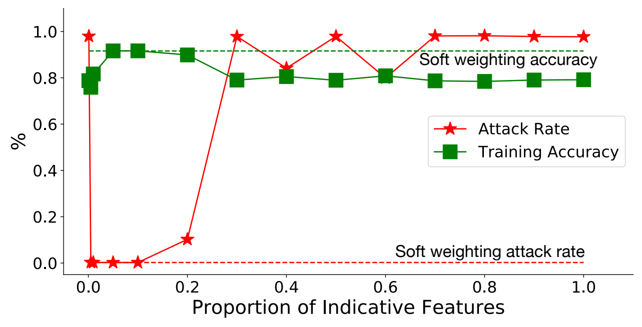


Figure 8. The performance of the optimal noisy attack on MNIST with varying indicative feature ratio.

observe that when using all of the features for similarity (far right), the poisoning attack is successful.

Once the proportion of indicative features decreases below 0.1 (10%), the dissimilarity caused by the intelligent noise is removed from the cosine similarity and the poisoning vector dominates the similarity, causing the intelligent noise strategy to fail with an attack rate of near 0. We also observe that if the proportion of indicative features is too low (0.01), the training accuracy also begins to suffer. When considering such a low number of features, honest clients appear to collude as well, causing false positives.

We also evaluated the soft feature weighing mechanism, which weighs each contribution proportionally based on the model parameter itself. The results of the soft weighting method on the same intelligent MNIST poisoning attack are also shown in Figure 8. For both the attack rate and training accuracy, the performance of the soft mechanism is comparable to the optimal hard filtering mechanism.

Adaptive updates method. We devised another optimal attack against FoolsGold that manipulates its memory component. If an adversary knows that FoolsGold employs cosine similarity on the update history, and is able to locally compute the pairwise cosine similarity among sybils, they can bookkeep this information and decide to send poisoned updates only when their similarity is sufficiently low (Algorithm 2). This algorithm uses a parameter M, representing the inter-sybil cosine similarity threshold. When M is low, sybils are less likely to be detected by FoolsGold as they will send their updates less often; however, this will also lower the influence each sybil has on the global model.

An adversary could generate an exceedingly large number of sybils for a successful attack, but given that the adversary is uncertain about the influence needed to overpower the honest clients, this becomes a difficult trade-off to navigate for an optimal attack.

To demonstrate this, the intelligent noise attack above is executed by 2 sybils on MNIST, with FoolsGold using the soft weighing of features in its cosine similarity (the optimal defense for MNIST against the intelligent noise attack). Figure 9 shows the relationship between M and the resulting expected ratio of sybils needed to match the influence for each honest opposing client.

For instance, if we observed that the sybils only sent poisoning gradients 25% of the time, they would need 4 sybils. Given a prescribed similarity threshold M, the values shown are the expected number of sybils required for the optimal attack. The attack is optimal because using less sybils does not provide enough influence to poison the model, while using more sybils is inefficient.

This is shown on Figure 9 by the three shaded regions: in the green region to the right ($M > 0.27$), the threshold is too high and any poisoning attack is detected and removed. In the blue region on the bottom left, the attack is not detected, but there is an insufficient number of sybils to overpower the honest opposing clients. Lastly, in the top left red region, the attack succeeds, potentially with more sybils than required.

```
    Data: Desired $\Delta_t$ from all sybils at iteration $t$,
          similarity threshold $M$
 1  for iteration $t$ do
 2      for All sybils $i$ do
            // Compute local history
 3          Let $H_i$ be the aggregate historical vector
              $\sum_{t=1}^{T} \Delta_{i,t}$
            // Feature Importance and similarity
 4          Let $S_t$ be the set of indicative features at
              iteration $t$ (if known)
 5          for All other sybils $j$ do
 6              Let $cs_{ij}$ be the $S_t$-weighted cosine
                  similarity between $H_i$ and $H_j$
 7
 8          end
 9      end
10      for All sybils $i$ do
            // Decision using row-wise maximum
11          if $\max_j(cs_i) > M$ then
12              Send intelligent noise vector $\zeta$
13          end
14          else
15              Send $\Delta_t$ to server
16          end
17      end
18  end
```
Algorithm 2: Adaptive attack on FoolsGold.

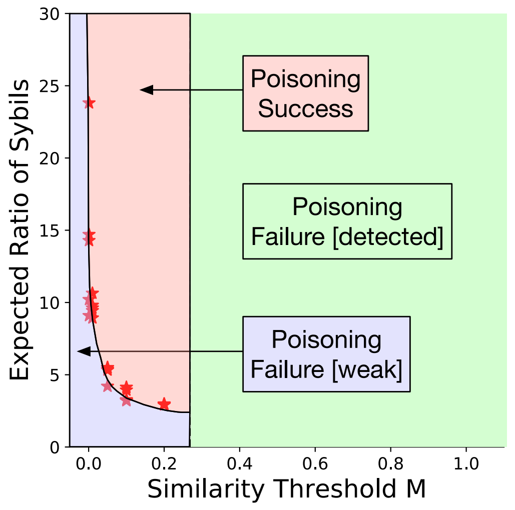


Figure 9. Relationship between similarity threshold and expected ratio of sybils per honest opposing client for the adaptive attack on FoolsGold (Alg. 9) with 2 sybils on MNIST.

With a sufficiently large number of sybils and appropriately low threshold, attackers can subvert our current defense for our observed datasets. Finding the appropriate threshold is challenging as it is dependent on many other factors: the number of honest clients in the system, the proportion of indicative features considered by FoolsGold, and the distribution of data.

Furthermore, this attack requires a higher proportion of sybils than the baseline poisoning attack on federated learning. For example, when M is set to 0.01, an attacker would require a minimum of 10 sybils per opposing client to poison the model, whereas in federated learning, they would only need to exceed the number of opposing clients. The exact number of sybils required to successfully poison the model is unknown to attackers without knowledge of the number of honest clients and their honest training data.

6.5. Effects of design elements

Each of the three main design elements (history, pardoning and logit) described in Section 4 addresses specific challenges. In the following experiments we disabled one of the three components and recorded the training error, attack rate, and target class error of the resulting model.

History. The two subversion strategies in the previous section increase the variance of updates in each iteration. The increased variance in the updates sent by sybils cause the cosine similarities at each iteration to be an inaccurate approximation of a client's sybil likelihood. Our design uses history to address this issue, and we evaluate it by comparing the performance of FoolsGold with and without history using an A-5 MNIST attack with 80% poisoned data and batch size of 1 (two factors which were previously shown to have a high variance).

Pardoning. We claim that honest client updates may be similar to the updates of sybils, especially if the honest client owns the data for the targeted class. To evaluate the necessity and efficacy of our pardoning system, we compare the performance of FoolsGold on KDDCup with the A-AllOnOne attack with and without pardoning.

Logit. An important motivation for using the logit function is that adversaries can arbitrarily increase the number of sybils to mitigate any non-zero weighting of their updates. We evaluate the performance of FoolsGold with and without the logit function for the A-99 MNIST attack.

Figure 10 shows the overall training error, sybil attack rate, and target class error for the six different evaluations. The attack rate for the A-AllOnOne KDDCup attack is the average attack rate for the 5 sets of sybils.

Overall, the results align with our claims. Comparing the A-5 MNIST case with and without history, we find that history successfully mitigates attacks that otherwise would pass through in the no-history system. Comparing the results of the A-AllOnOne KDDCup attack, we find that, without pardoning, the training error and target class error increase while the attack rate was negligible for both cases, indicating a high rate of false positives for the target class. Finally, comparing the results for the A-99 MNIST attack, without the logit function, the adversary was able to mount a successful attack by overwhelming FoolsGold with sybils, showing that the logit function is necessary to prevent this attack.

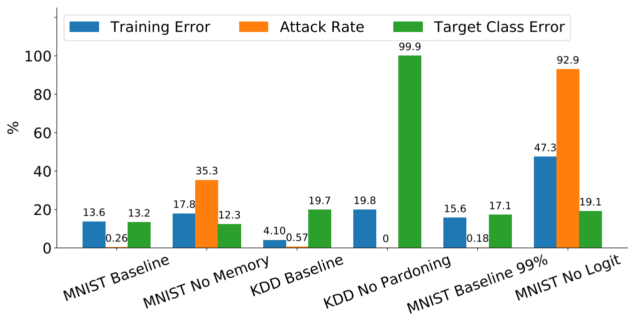


Figure 10. Metrics for FoolsGold with various components independently removed.

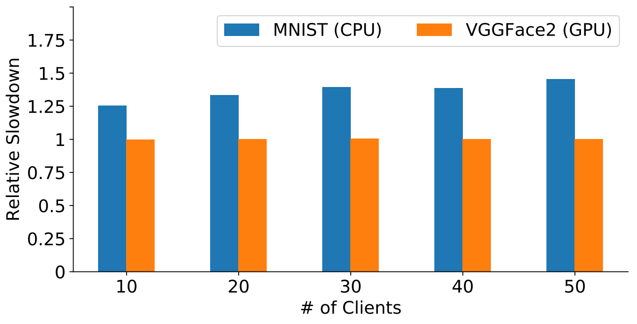


Figure 11. Running time overhead of FoolsGold as compared to Federated Learning (baseline of 1), for MNIST (on a CPU) and VGGFace2 (on a GPU).

6.6. FoolsGold performance overhead

We evaluate the runtime overhead incurred by augmenting a federated learning system with FoolsGold. We run the system with and without FoolsGold with 10 – 50 clients by training an MNIST classifier on a commodity CPU and a VGGFace2 deep learning model on a Titan V CPU.

Figure 11 plots the relative slowdown added by FoolsGold for CPU and GPU based workloads. On a CPU, the most expensive part of the FoolsGold algorithm is computing the pairwise cosine similarity. Our Python prototype is not optimized and there are known optimizations to improve the speed of computing angular distance at scale [2]. When training a deep learning model on a GPU, the cost of training is high enough that the relative slowdown from FoolsGold is negligible. We profiled micro-benchmarks for the total time taken to execute the FoolsGold algorithm and found that it took less than 1.5 seconds, even with 50 clients.

7. Limitations

Combating a single client adversary. FoolsGold is designed to counter *sybil-based attacks* and our results in Figure 5 indicate that FoolsGold is not successful at mitigating attacks mounted by a single poisoning client.

However, we note that a single malicious actor could be detected and removed by Multi-Krum [10]. Though Multi-Krum is not designed for and does poorly in the non-IID setting, we performed an experiment in which FoolsGold was augmented with a properly parameterized Multi-Krum solution, with $f = 1$.

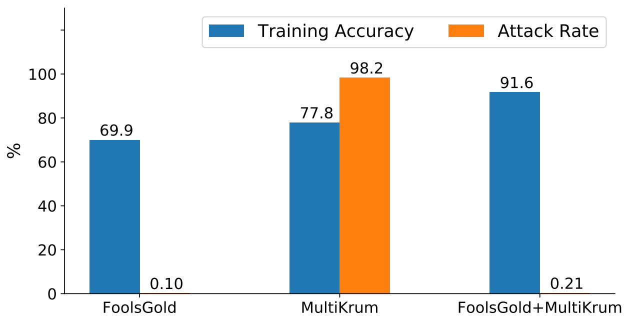


Figure 12. The performance of Multi-Krum with FoolsGold when combating the optimal strawman attack on MNIST.

We consider an ideal strawman attack in which a single adversarial client sends the vector to the poisoning objective at each iteration. This attack does not require sybils and can therefore bypass FoolsGold. Figure 12 shows the training accuracy and the attack rate for FoolsGold, Multi-Krum, and the two systems combined when facing a concurrent A-5 and the ideal strawman attacks.

When Multi-Krum uses $f = 1$ and FoolsGold is enabled, we see that Multi-Krum and FoolsGold do not interfere with each other. The Multi-Krum algorithm prevents the strawman attack, and FoolsGold prevents the sybil attack. Independently, these two systems fail to defend both attacks concurrently, either by failing to detect the ideal strawman attack (against FoolsGold) or by allowing the sybils to overpower the system (against Multi-Krum).

FoolsGold is specifically designed for handling poisoning attacks from a group of sybils: we believe current state of the art is better suited to mitigate attacks from single actors.

Improving FoolsGold against informed attacks. In Figure 9, we observe that FoolsGold can be subverted by a knowledgeable adversary with many sybils. We believe that non-determinism may further help to improve FoolsGold. For example, by using a weighted random subset of gradients in the history mechanism or by measuring similarity across random subsets of client contributions. With more randomness, it is more difficult for intelligent adversaries to use knowledge about FoolsGold's design to their advantage.

Another solution is to use a better similarity metric. This includes strategies from prior work such as incorporating graph-based similarity [41], using auxiliary information from a client dataset [39], or mandating a minimum similarity score to reject anomalous contributions. While more informed, these solutions also require more assumptions about the nature of the attack.

8. Related work

We reviewed Multi-Krum [10] as the state of the art defense against poisoning in federated learning. Here we review the broader literature on secure ML, sybils, and poisoning.

Secure ML. Another approach to mitigating sybils in federated learning is to make the overall system more secure. Trusted execution environments, such as SGX are an alternative solution [33]. However, we note that sybil-based poisoning can be performed at the data input level, which is *not* secured by SGX. Even in a secure enclave running trusted code, a poisoning attack can be performed through malicious data. FoolsGold can be added to systems based on SGX to prevent sybil attacks.

Other solutions employ data provenance to prevent poisoning attacks [5] by segmenting, identifying, and removing training data from the model that is likely malicious. This solution requires extra assumptions about how training data is collected and in federated learning, where many clients supply data from a variety of sources, this assumption is unrealistic.

Sybil defenses. One way to mitigate sybils is to use proof of work [3], in which a client must solve a computationally expensive problem (that is easy to check) to contribute to the system. Recent alternatives have explored the use of proof of stake [19], which weighs clients by the value of their *stake* in the system.

Some approach actively detect and remove sybils using auxiliary information, such as an underlying social network [38], or detect and reject malicious behavior [39], [40]. Many sybil detection strategies map the interactions between clients into a weighted graph and use sybil defenses from social networks [41] as a reduction. However, federated learning limits the amount of information exposed to the central service, and these defenses may rely on privacy-compromising information. By contrast, FoolsGold does not use any auxiliary information outside of the learning process.

Other ML poisoning defenses. Another poisoning defense involves bagging classifiers [8] to mitigate the effects of outliers in the system. These defenses are effective in scenarios where the dataset is centralized, but are complex to apply in a federated learning setting, where access to the data is prohibited. This algorithm also assumes control of the gradient computation during training.

AUROR [36] is a defense designed for the multi-party ML setting. It defines indicative features to be the most important model features, and a distribution of modifications to them is collected and fed to a clustering algorithm. Contributions from small clusters that exceed a threshold distance are removed. This clustering assumes that the majority of updates to that feature come from honest clients for all indicative features. Unlike AUROR, FoolsGold assumes the presence of sybils and uses gradient similarity to detect anomalous clients.

9. Conclusion

The decentralization of ML is driven by growing privacy and scalability challenges. Federated learning is a state of the art proposal adopted in production [27]. However, such decentralization opens the door for malicious clients to participate in training. We considered the problem of poisoning attacks by sybils to achieve a poisoning objective. We show that existing defenses to such attacks are ineffective and propose *FoolsGold*, a defense that uses client *contribution similarity*.

Our results indicate that FoolsGold can mitigate a variety of attack types and is effective even when sybils overwhelm honest users. We also considered advanced attack types in which sybils mix poisoned data with honest data, add intelligent noise to their updates, and adaptively rate limit their poisoned updates to avoid detection. Across all scenarios, our defense is able to outperform prior work.

FoolsGold minimally changes the federated learning algorithm, relies on standard techniques such as cosine similarity, and does not require prior knowledge of the expected number of sybils. We hope that our work inspires further research on defenses that are co-designed with the underlying learning procedure.

References

[1] M. Ancona, E. Ceolini, A. C. Oztireli, and M. Gross, "A unified view of gradient-based attribution methods for deep neural networks," in *Workshop on Interpreting, Explaining and Visualizing Deep Learning*, ser. NIPS, 2017.

[2] A. Andoni, P. Indyk, T. Laarhoven, I. Razenshteyn, and L. Schmidt, "Practical and optimal lsh for angular distance," in *Advances in Neural Information Processing Systems 28*, ser. NIPS, 2015.

[3] A. Back, "Hashcash - A Denial of Service Counter-Measure," Tech. Rep., 2002.

[4] E. Bagdasaryan, A. Veit, Y. Hua, D. Estrin, and V. Shmatikov, "How To Backdoor Federated Learning," *ArXiv e-prints*, 2018.

[5] N. Baracaldo, B. Chen, H. Ludwig, and J. A. Safavi, "Mitigating poisoning attacks on machine learning models: A data provenance based approach," in *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, ser. AISec, 2017.

[6] M. Barreno, B. Nelson, A. D. Joseph, and J. D. Tygar, "The Security of Machine Learning," *Maching Learning*, vol. 81, no. 2, 2010.

[7] B. Biggio, B. Nelson, and P. Laskov, "Support vector machines under adversarial label noise," in *Proceedings of the Asian Conference on Machine Learning*, 2011.

[8] B. Biggio, I. Corona, G. Fumera, G. Giacinto, and F. Roli, "Bagging classifiers for fighting poisoning attacks in adversarial classification tasks," in *Multiple Classifier Systems*, 2011.

[9] B. Biggio, B. Nelson, and P. Laskov, "Poisoning Attacks Against Support Vector Machines," in *Proceedings of the 29th International Coference on International Conference on Machine Learning*, 2012.

[10] P. Blanchard, E. M. El Mhamdi, R. Guerraoui, and J. Stainer, "Machine learning with adversaries: Byzantine tolerant gradient descent," in *Advances in Neural Information Processing Systems 30*, ser. NIPS, 2017.

[11] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, "Practical secure aggregation for privacy-preserving machine learning," in *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, ser. CCS, 2017.

[12] L. Bottou, "Large-Scale Machine Learning with Stochastic Gradient Descent," in *19th International Conference on Computational Statistics*, ser. COMPSTAT, 2010.

[13] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "Vggface2: A dataset for recognising faces across pose and age," in *International Conference on Automatic Face and Gesture Recognition*, ser. FG, 2018.

[14] X. Chen, C. Liu, B. Li, K. Lu, and D. Song, "Targeted backdoor attacks on deep learning systems using data poisoning," *ArXiv e-prints*, 2017.

[15] A. Datta, S. Sen, and Y. Zick, "Algorithmic transparency via quantitative input influence: Theory and experiments with learning systems," in *Proceedings of the 2016 IEEE Symposium on Security and Privacy*, ser. S&P, 2016.

[16] D. Dheeru and E. Karra Taniskidou, "UCI machine learning repository," 2017. [Online]. Available: http://archive.ics.uci.edu/ml

[17] J. J. Douceur, "The sybil attack," in *IPTPS*, 2002.

[18] R. C. Geyer, T. Klein, and M. Nabi, "Differentially private federated learning: A client level perspective," *NIPS Workshop: Machine Learning on the Phone and other Consumer Devices*, 2017.

[19] Y. Gilad, R. Hemo, S. Micali, G. Vlachos, and N. Zeldovich, "Algorand: Scaling byzantine agreements for cryptocurrencies," in *Proceedings of the 26th Symposium on Operating Systems Principles*, ser. SOSP, 2017.

[20] T. Gu, B. Dolan-Gavitt, and S. Garg, "BadNets: Identifying Vulnerabilities in the Machine Learning Model Supply Chain," *ArXiv e-prints*, 2017.

[21] B. Han, I. W. Tsang, and L. Chen, "On the convergence of a family of robust losses for stochastic gradient descent," in *European Conference on Machine Learning and Knowledge Discovery in Databases - Volume 9851*, ser. ECML PKDD, 2016.

[22] B. Hitaj, G. Ateniese, and F. Pérez-Cruz, "Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning," in *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, 2017.

[23] L. Huang, A. D. Joseph, B. Nelson, B. I. Rubinstein, and J. D. Tygar, "Adversarial Machine Learning," in *Proceedings of the 4th ACM Workshop on Security and Artificial Intelligence*, 2011.

[24] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, 1998.

[25] S. Marcel and Y. Rodriguez, "Torchvision the machine-vision package of torch," in *Proceedings of the 18th ACM International Conference on Multimedia*, ser. MM, 2010.

[26] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, 2017.

[27] H. B. McMahan and D. Ramage, "Federated Learning: Collaborative Machine Learning without Centralized Training Data," https://research.googleblog.com/2017/04/federated-learning-collaborative.html, 2017, accessed: 2017-10-12.

[28] M. Mozaffari-Kermani, S. Sur-Kolay, A. Raghunathan, and N. K. Jha, "Systematic Poisoning Attacks on and Defenses for Machine Learning in Healthcare," in *IEEE Journal of Biomedical and Health Informatics*, 2015.

[29] D. Needell, R. Ward, and N. Srebro, "Stochastic gradient descent, weighted sampling, and the randomized kaczmarz algorithm," in *Advances in Neural Information Processing Systems 27*, 2014.

[30] B. Nelson, M. Barreno, F. J. Chi, A. D. Joseph, B. I. P. Rubinstein, U. Saini, C. Sutton, J. D. Tygar, and K. Xia, "Exploiting Machine Learning to Subvert Your Spam Filter," in *Proceedings of the 1st Usenix Workshop on Large-Scale Exploits and Emergent Threats*, 2008.

[31] A. Nemirovski, A. Juditsky, G. Lan, and A. Shapiro, "Robust stochastic approximation approach to stochastic programming," *SIAM J. on Optimization*, vol. 19, pp. 1574–1609, 2009.

[32] A. Nitin Bhagoji, S. Chakraborty, P. Mittal, and S. Calo, "Analyzing Federated Learning through an Adversarial Lens," *arXiv e-prints*, 2018.

[33] O. Ohrimenko, F. Schuster, C. Fournet, A. Mehta, S. Nowozin, K. Vaswani, and M. Costa, "Oblivious Multi-Party Machine Learning on Trusted Processors," in *USENIX SEC*, 2016.

[34] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[35] B. I. Rubinstein, B. Nelson, L. Huang, A. D. Joseph, S.-h. Lau, S. Rao, N. Taft, and J. D. Tygar, "ANTIDOTE: Understanding and Defending Against Poisoning of Anomaly Detectors," in *IMC*, 2009.

[36] S. Shen, S. Tople, and P. Saxena, "Auror: Defending against poisoning attacks in collaborative deep learning systems," in *Proceedings of the 32Nd Annual Conference on Computer Security Applications*, ser. ACSAC, 2016.

[37] R. Shokri and V. Shmatikov, "Privacy-preserving deep learning," in *Proceedings of the 2015 ACM SIGSAC Conference on Computer and Communications Security*, ser. CCS, 2015.

[38] N. Tran, B. Min, J. Li, and L. Subramanian, "Sybil-resilient online content voting," in *Proceedings of the 6th USENIX Symposium on Networked Systems Design and Implementation*, ser. NSDI, 2009.

[39] B. Viswanath, M. A. Bashir, M. B. Zafar, S. Bouget, S. Guha, K. P. Gummadi, A. Kate, and A. Mislove, "Strength in numbers: Robust tamper detection in crowd computations," in *Proceedings of the 3rd ACM Conference on Online Social Networks*, ser. COSN, 2015.

[40] G. Wang, B. Wang, T. Wang, A. Nika, H. Zheng, and B. Y. Zhao, "Defending against sybil devices in crowdsourced mapping services," in *Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys, 2016.

[41] H. Yu, P. B. Gibbons, M. Kaminsky, and F. Xiao, "Sybillimit: A near-optimal social network defense against sybil attacks," *IEEE/ACM Transactions on Networking*, 2010.

[42] M. D. Zeiler, "ADADELTA: An Adaptive Learning Rate Method," *ArXiv e-prints*, 2012.

Appendix A: Convergence analysis

Theorem: Given the process in Algorithm 1, the convergence rate of the participants (malicious and honest) is $O(\frac{1}{T^2})$ over T iterations.

Proof of theorem: We know from the convergence analysis of SGD [31] that for a constant learning rate, we achieve a $O(\frac{1}{T^2})$ convergence rate.

Let M be the set of malicious clients in the system and G be the set of honest clients in the system. Assume that the adapted learning rates provided at each iteration α_i are provided by a function $h(i,t)$, where i is the client index and t is the current training iteration. As long as $h(i,t)$ does not modify the local learning rate of the honest clients and removes the contributions of sybils, the convergence analysis of SGD applies as if the training was performed with the honest clients' data.

$$\forall i \in M, h(i,t) \rightarrow 0 \qquad \text{(cond1)}$$
$$\forall i \in G, h(i,t) \rightarrow 1 \qquad \text{(cond2)}$$

We will show that, under certain assumptions, FoolsGold satisfies both conditions of $h(i,t)$. We prove each condition separately.

Condition 1: Let v_i be the ideal gradient for any given client i from the initial shared global model w_0, that is: $w_0 + v_i = w_i^*$ where w_i^* is the optimal model relative to any client i's local training data. Since we have defined all sybils to have the same poisoning goal, all sybils will have the same ideal gradient, which we define to be v_m.

As the number of iterations in FoolsGold increases, the historical gradient $H_{i,t}$ for each sybil approaches v_m, with error from the honest client contributions ϵ:

$$\forall i \in M : \lim_{t\rightarrow\infty} H_{i,t} = v_m + \epsilon$$

Since the historical update tends to the same vector for all sybils, the expected pairwise similarity of these updates will increase as the learning process continues. As long as the resulting similarity, including the effect of pardoning between sybils, is below β_m, FoolsGold will adapt the learning rate to 0, satisfying (cond1).

β_m is the point at which the logit function is below 0 and is a function of the confidence parameter κ:

$$\beta_m \geq 1 - \frac{e^{-0.5\kappa}}{1+e^{-0.5\kappa}}$$

Condition 2: Regarding the ideal gradients of honest clients, we assume that the maximum pairwise cosine similarity between the ideal gradient of honest clients is β_g. As long as β_g is sufficiently low such that FoolsGold assigns a learning rate adaptation of 1 for all honest clients, the second condition of $h(i,t)$ is met. β_g is the point at which the logit function is greater than 1 and is also a function of the confidence parameter κ:

$$\beta_g \leq 1 - \frac{e^{0.5\kappa}}{1+e^{0.5\kappa}}$$

If the above condition holds, FoolsGold will classify these clients to be honest and will not modify their learning rates. This maintains the constant learning rate and satisfies (cond2).

Appendix B: Additional Evaluations

Comparison to RONI. A Reject on Negative Influence (RONI) defense [6] counters ML poisoning attacks. When evaluating a set of suspicious training examples, this defense trains two models: one model using a trusted dataset, and another model using the union of the trusted and suspicious data. If the performance of the model degrades the performance beyond a specified threshold, the data is rejected.

RONI has not been applied to federated learning before. To extend RONI to a federated learning setting, the server can capture the influence of a single update, rather than an entire dataset. RONI is ineffective in this setting because, at any given iteration, an honest gradient may update the model in an incorrect direction, resulting in a drop in validation accuracy. This is confounded by the problem that clients may have data that is not accurately modeled by the RONI validation set. For example, we can see in Table 1 that the prediction accuracy across the other nine digits only dropped slightly when executing a poisoning attack in a non-IID setting. Depending on the RONI threshold, this poisoning attack may go undetected.

We show that using RONI with a validation dataset that contains a uniform distribution of data, is insufficient in countering sybil-based poisoning in a non-IID setting.

We train an MNIST classifier and use a 10,000 example IID RONI validation set. We perform an A-5 1-7 attack on the system and log the total RONI validation score across all 15 clients (10 honest and 5 sybils) for 3,000 iterations. Figure 13 shows the total sum of the RONI score across all iterations (the 5 right-most clients in the Figure are sybils). A RONI score below 0 indicates rejection. Figure 13 shows that all clients except the honest client with the digit 1 had received a negative score in every iteration.

In the non-IID setting, clients send updates that do not represent an update from the global data distribution. Validating individual updates from a single client in such a fashion produces false positives because the aggregator holds a validation set that contains uniform samples, and RONI flags each of their updates as malicious for doing poorly on the validation set.

Without prior knowledge of the details of a potential attack, RONI is unable to distinguish between updates coming from sybils and updates coming from honest non-IID clients.

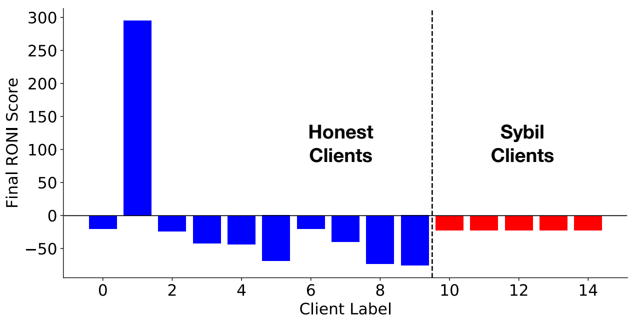


Figure 13. The final sum of the RONI validation scores for the A-5 attack executed on federated learning: RONI is unable to distinguish the malicious clients (5 rightmost) from most of the honest ones (the first 10).

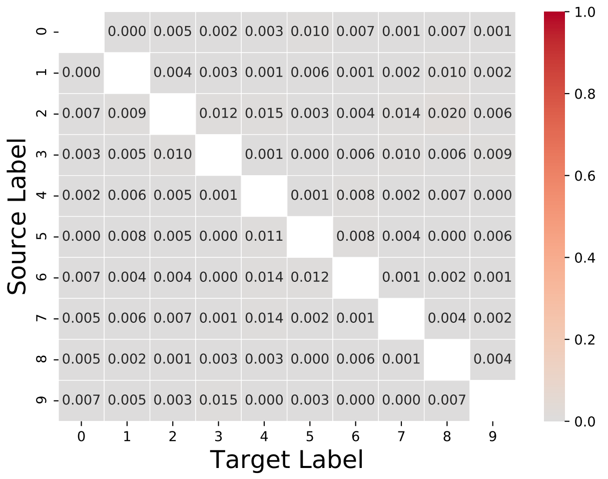


Figure 14. The attack rates for the A-5 attack executed for all combinations: attempting to mis-label a true (source) 0-9 class to a different (target) 0-9 class.

Attack generalization. In this work, we have used the 1-7 attack on MNIST as our running example. However, the attacker could be more successful in attacking a different source and target class. We evaluate FoolsGold's ability to generalize to other targeted poisoning attacks against MNIST (i.e., all other possible source and target MNIST labels) For each possible source-target combination, we execute the A-5 attack scenario against FoolsGold.

Figure 14 shows the resulting attack rate for our defense across all permutations of the A-5 MNIST poisoning attacks.

The highest attack rate observed across all source-target combinations is 0.02, indicating that FoolsGold generalizes to other class-based poisoning attacks in MNIST.

Backdoor attacks. To demonstrate the applicability of FoolsGold towards backdoor sybil attacks, we repeat the baseline evaluation against the single pixel backdoor attack [20]. To perform this attack, a random subset of the MNIST training data is marked with a white pixel in the bottom-right corner of the image, and labelled as a 7. A successful backdoor attack results in a model where all images with the backdoor inserted (a white bottom-right pixel) would be predicted as 7s, regardless of the other information in the image.

The backdoor attack becomes stronger when a higher proportion of the training data is poisoned [20]; we view

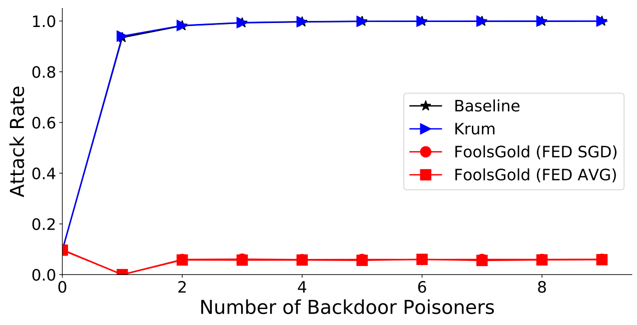


Figure 15. Backdoor attack rate for varying number of sybils, for federated learning (Baseline), Multi-Krum, and FoolsGold.

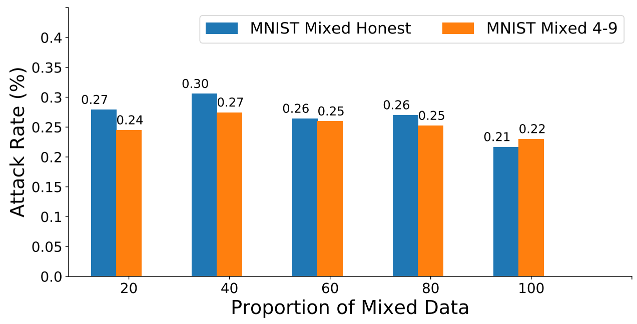


Figure 16. Sybils cannot subvert FoolsGold by including a proportion of different honest or attack data.

this as identical to increasing the number of sybils in the system, who all possess a random subset of the original training data with the backdoor inserted. The single pixel backdoor was applied with an increasing number of poisoners (from 0 to 9), against a system with FoolsGold, Multi-Krum or federated learning. In this experiment, Multi-Krum was also configured such that the parameter f was equal to the number of sybils in the system.

The results of the sybil-based backdoor attack are shown in Figure 15. FoolsGold is also effective in defending against the backdoor attack from a large number of sybils, for FEDSGD and FEDAVG.

Since the sybils are all performing the same attack, in which all classes are being backdoored to the same class, the similarities between these updates will be higher than the similarities between honest clients.

As in the label-flipping evaluation, there was a high degree of false positives in FoolsGold when being attacked by only one backdooring client. While the attack rate was 0, the resulting test accuracy was below 80% (due to low prediction rate of 7s).

Resilience to mixed data. Attackers may attempt to subvert our design by creating a dataset with a mixture of honest and poisoned data. This provides an opportunity for sybils to appear honest, as they are less similar when executing SGD. Note that in this case the attacker purposefully mitigates their attack by labeling a proportion of the poisoned dataset *correctly*.

To evaluate this attack, we created datasets with 20%, 40%, 60% and 80% poisoned data for an MNIST 1-7 attack, and the remaining proportion of the data with honestly labeled data. We also perform a second experiment in which the attacker mixes their data with poisoned data for a second 4-9 attack, effectively performing a mixture

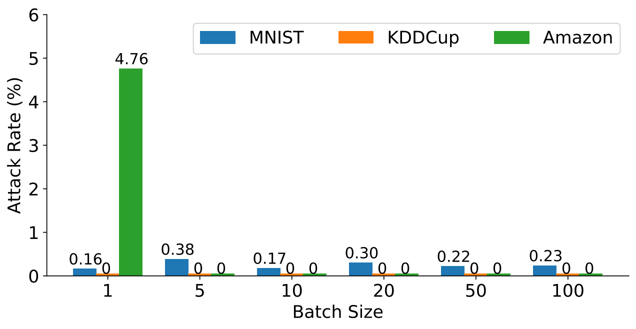


Figure 17. The performance of the A-5 attack on all datasets with increasing batch size.

of two targeted poisoning datasets simultaneously. Both attacks are mounted using the A-5 strategy.

Figure 16 plots the attack rate against the proportion of mixing. This attack was performed with KDDCup and Amazon datasets, for which all attack rates are 0; we omit these results. We observe that FoolsGold is robust to this strategy: the amount of data mixing does not impact FoolsGold's ability to mitigate sybils, when choosing any proportion between 20% and 80%, the maximum average attack rate observed is 0.003.

At any individual iteration, sybils are more likely to appear as honest clients. However, as the number of iterations increases, the average will tend to the same objective, which FoolsGold is able to detect through its use of history. The effect of this mechanism is explored more in Section 6.5.

Resilience to different batch sizes. Another factor that impacts FoolsGold's effectiveness is the client batch size. Given that variance in SGD decreases with more data points, we expect FoolsGold to perform worse with smaller batch sizes.

To evaluate different batch sizes, we performed A-5 attacks on all three datasets. In each case, all clients and sybils perform SGD with the same batch size for values of 1, 5, 10, 20, 50, and 100. Since no Amazon data partition contains over 50 examples, we do not evaluate Amazon with batch sizes of 50 and 100.

Figure 17 shows the attack rate as the batch size increases. It shows that FoolsGold is resilient to the batch size for A-5 attacks performed on MNIST and KDDCup, achieving an attack rate at or near 0.

The only instance in which performance of the system suffered was for the A-5 Amazon attack with the batch size set to 1; the resulting attack rate was 4.76%. This is due to the curse of dimensionality: there is a higher variance in the similarities between updates when the dimension size is large (10,000). This variance is maximal when the batch size is lowest.